RESEARCH PAPER

Opposition based competitive grey wolf optimizer for EMG feature selection

Jingwei Too[1] · Abdul Rahim Abdullah[1]

Abstract

This paper proposes a competitive grey wolf optimizer (CGWO) to solve the feature selection problem in electromyography (EMG) pattern recognition. We model the recently established feature selection method, competitive binary grey wolf optimizer (CBGWO), into a continuous version (CGWO), which enables it to perform the search on continuous search space. Moreover, another new variant of CGWO, namely opposition based competitive grey wolf optimizer (OBCGWO), is proposed to enhance the performance of CGWO in feature selection. The proposed methods show superior results in several benchmark function tests. As for EMG feature selection, the proposed algorithms are evaluated using the EMG data acquired from the publicly access EMG database. Initially, several useful features are extracted from the EMG signals to construct the feature set. The proposed CGWO and OBCGWO are then applied to select the relevant features from the original feature set. Four state-of-the-art algorithms include particle swarm optimization, flower pollination algorithm, butterfly optimization algorithm, and CBGWO are used to examine the effectiveness of proposed methods in feature selection. The experimental results show that OBCGWO can provide optimal classification performance, which is suitable for rehabilitation and clinical applications.

Keywords Feature selection · Optimization · Competitive binary grey wolf optimizer · Electromyography · Classification · Opposition learning

1 Introduction

Electromyography (EMG) signal is one of the biomedical signals that expressed muscular activity during motions. EMG signal offers much useful information related to muscle condition, and it has received much attention in the pattern recognition system such as myoelectric prosthetic [1]. Myoelectric control makes use of EMG signals as the control source to activate the prosthesis, which allows the amputees to perform several basic hand motions in their daily living [2, 3]. Nevertheless, the quality of extracted features has a strong influence on the classification performance. This is because the features will characterize the pattern of recorded EMG signals according to the similarity and repeatability

of motions [4]. Therefore, the choice of features is critically important in EMG signals classification.

In fact, the selection of features is considered as *NP* hard combinatorial problem in which the number of possible solutions increases exponentially with the number of features. Hence, it is impractical to perform the exhaustive search during a high dimensional feature vector [5]. For such reason, feature selection can be an essential step to solve the high dimensionality problem. Feature selection is a process of determining the subset of potential features that can best describe the target concept in the classification stage. It is not only improving the classification performance but also eliminating some of the redundant and irrelevant features [6, 7].

In general, feature selection can be categorized into filter and wrapper methods. The former identifies the relevant features based on the information theory and distance measurement, whereas the latter uses the optimization algorithm and a specific learning algorithm in the process of evaluation [7, 8]. As compared to the filter method, wrapper based feature selection can usually provide better

✉ Jingwei Too
  jamesjames868@gmail.com

1   Faculty of Electrical Engineering, Universiti Teknikal
    Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal,
    Melaka, Malaysia

classification performance, which becomes the major interest of researchers in feature selection. In the past study, Ramos et al. [9] introduced the harmony search to identify the best combination of relevant features. Emary et al. [10] proposed two novel binary grey wolf optimizations to solve the feature selection tasks. Ewees et al. [11] developed a new chaotic multi-verse optimizer with five different chaotic maps for feature selection. Moreover, Tan et al. [12] proposed an enhanced particle swarm optimization to tackle the feature selection problem in skin cancer detection. Previous works reported that the utilization of feature selection methods can effectively eliminate the irrelevant and redundant features, thus leading to optimal classification results.

Recently, a competitive binary grey wolf optimizer (CBGWO) has proposed to solve the feature selection problem in EMG signals classification [13]. The CBGWO is a variant of the grey wolf optimizer, which has proven to be superior against other conventional feature selection methods. In addition, CBGWO has the advantage of simplicity and low computational complexity. Beneficial its excellent performance, CBGWO can be useful for many engineering applications. However, CBGWO is only applicable to binary optimization problems, but not to the continuous optimization tasks. From the point of view, the functionality of CBGWO in worldwide applications has limited.

In this paper, we aim to model the CBGWO into a continuous version, which enables it to perform the search on the continuous search space. The proposed method is named as competitive grey wolf optimizer (CGWO). However, CGWO does not guarantee performance enhancement in feature selection. Therefore, we propose another variant of CGWO, namely opposition based competitive grey wolf optimizer (OBCGWO) to tackle the feature selection problem in EMG signals classification. The OBCGWO integrates the opposition based learning (OBL) strategy to boost the performance of CGWO. Initially, an OBL based initialization is introduced to enhance the quality of initial solutions. Later, an OBL based position updating strategy is proposed to improve the explorative behavior of the algorithm, which enables OCGWO to explore the untried areas to find the global optimum. In the first part of the experiment, several benchmark functions are used to test the performance of proposed CGWO and OBCGWO in optimization. In the second part of the experiment, the proposed methods are applied to solve the EMG feature selection problems. The EMG data of eight subjects acquired from the publicly access EMG database is used in this work. Four state-of-the-art methods include particle swarm optimization (PSO), butterfly optimization algorithm (BOA), flower pollination algorithm (FPA), and CBGWO are used to evaluate the effectiveness of proposed OBCGWO in feature selection. The experimental results illustrate that OBCGWO is able to offer competitive performance as compared to CGWO and other conventional methods.

The rest of paper is organized as follows: Sect. 2 describes the materials and methods, which includes the EMG data, feature extraction, the proposed CGWO and OBCGWO, and their application in EMG feature selection. Section 3 discusses the findings of the research. Finally, Sect. 4 concludes the findings of this work.

2 Materials and methods

2.1 EMG data

The EMG data are acquired from the public access 10mov-4chUF_AFEs Dataset via the Biopatrec Repository [14]. This study utilizes the EMG database with TI ADS1299 configuration that composed the EMG signals of ten different hand and wrist motions (hand open, hand close, wrist flex, wrist extend, pro, supination, side grip, fine grip, agree, and pointer) recorded from eight healthy subjects. In the experiment, four bipolar electrodes (four channels) were used to record the EMG signals. The subject was asked to perform the hand motion for 3 s with 3 s of relaxation. Each hand motion was repeated for three trials, and the signals were sampled at 2000 Hz [15].

2.2 Feature extraction

The raw EMG signal is not suitable for classification since it composes a large quantity of data, and this may mislead the result [16]. Therefore, feature extraction is an essential step to obtain useful information by representing the raw EMG signal into a reduced set of features. In this study, the windowing technique is applied to segment the EMG signals due to lower computational cost and simplicity [17]. We adopted a window length of 200 ms with a 100 ms overlap.

In general, the EMG features can be categorized into time domain (TD), frequency domain (FD), and time–frequency domain (TFD) features. As compared to FD and TFD, TD features can be directly extracted from the EMG time series, which leads to low complexity and fast computation speed. Thus, TD features are more widely used in EMG studies [2, 18–20]. Moreover, some studies indicated that the combination of FD, TFD and TD features can further improve the performance of the classification model [17, 21, 22]. In the present work, we adopt thirty EMG features, as shown in Table 1. These features are selected due to their promising performances in previous works [17, 18, 23–26].

By performing the windowing, we obtain 870 EMG time series segments. Then, thirty features are extracted from each EMG segment and form a feature set. In total, 132 features (33 features × 4 channels) are extracted from each motion from

Table 1 Thirty EMG features used in this study

No.	Feature extracted	Abbr.	No.	Feature extracted	Abbr.
1	Mean absolute value	MAV	16	Maximum fractal length	MFL
2	Wavelength	WL	17	Skewness	SKEW
3	Slope sign change	SSC	18	Kurtosis	KURT
4	Zero crossing	ZC	19	Coefficient of variation	COV
5	Average amplitude change	AAC	20	Temporal moment (third order)	TM
6	Willison amplitude	WA	21	Difference absolute mean value	DAMV
7	Difference absolute standard deviation value	DASDV	22	Difference variance value	DVARV
8	Root mean square	RMS	23	Enhanced wavelength	EWL
9	Simple square integral	SSI	24	Enhanced mean absolute value	EMAV
10	Variance of EMG	VAR	25	Mean frequency	MNF
11	Log detector	LD	26	Median frequency	MDF
12	V-order (second order)	VO	27	Spectral moment (first order)	SM
13	Myopulse percentage rate	MYOP	28	Total power	TTP
14	Cardinality	CARD	29	Mean power	MNP
15	Integrated EMG	IEMG	30	Autoregressive mode (fourth order)	AR

each subject. Note that AR at the fourth-order generates four features, and thus resulting in 33 features. Finally, an EMG feature set that consists of 870 instances × 132 features is acquired from each subject.

2.3 Competitive binary grey wolf optimizer

Competitive binary grey wolf optimizer (CBGWO) is a recent feature selection method that has successfully applied to solve the feature selection problem in EMG signals classification [13]. Ordinarily, grey wolves live in a pack with an organization of 5–12 wolves. The main leader is known as alpha (α) wolf, followed by beta (β) and delta (δ) wolves. The rests are assumed to be omegas, which follow the leaders in the hunting and searching prey process [27]. The operation of CBGWO is described as follows:

Firstly, a population of grey wolves is randomly initialized (either 0 or 1). Secondly, the fitness values of wolves are evaluated, and the alpha, beta, and delta wolves are defined. In each iteration, the population of wolves is randomly partitioned into $N/2$ couples, where N is the population size. After this, there is a competition between two wolves in each couple. From the competition, the wolves that achieve better fitness values are known as winners, and they are directly passed into the new population. By contrast, the losers of the competition update their positions by learning from the winners and leaders. Mathematically, the position of the loser is updated as:

$$x^d(t+1) = \begin{cases} 1, & \text{if } S\left(\frac{x_1^d + x_2^d + x_3^d}{3}\right) \geq rand \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$S(x) = \frac{1}{1 - \exp(-10(x - 0.5))} \tag{2}$$

where *rand* is a random number distributed between 0 and 1, d is the dimension of search space, and S is the modified sigmoid function as in Eq. (2). The coefficients x_1, x_2, and x_3 are expressed as follows:

$$x_1 = x_\alpha - A_1 \cdot (D_\alpha) \tag{3}$$

$$x_2 = x_\beta - A_2 \cdot (D_\beta) \tag{4}$$

$$x_3 = x_\delta - A_3 \cdot (D_\delta) \tag{5}$$

where x_α, x_β, and x_δ are the position of alpha, beta, and delta at iteration t. The A_1, A_2 and A_3 are calculated using Eq. (6), and the D_α, D_β and D_δ are computed using Eqs. (7), (8) and (9), respectively.

$$A = 2y \cdot r_1 - y \tag{6}$$

$$D_\alpha = \left| C_1 x_\alpha - (x_w - x_l) \right| \tag{7}$$

$$D_\beta = \left| C_2 x_\beta - (x_w - x_l) \right| \tag{8}$$

$$D_\delta = \left| C_3 x_\delta - (x_w - x_l) \right| \tag{9}$$

where parameter y is linearly decreasing from 2 to 0, r_1 is a random number distributed between 0 and 1, x_w is the winner wolf, x_1 is the loser wolf, and C is defined as follow:

$$C = 2r_2 \tag{10}$$

where r_2 is a random number distributed between 0 and 1. After position updates, the fitness values of new losers are evaluated and passed into the new population. Then, the alpha, beta, and delta are updated.

At the end of each iteration, a leader enhancement process is executed. In this process, the leaders (alpha, beta, and delta) are allowed to enhance themselves by performing the random walk. Mathematically, the random walk can be computed as:

$$L^d = \begin{cases} rand(0,1), & \text{if } R \geq r_3 \\ X_L^d, & \text{otherwise} \end{cases} \tag{11}$$

where X_L is the leader (either alpha, beta or delta), $rand\,(0,1)$ is a random number generated either 0 or 1, r_3 is a random number distributed between 0 and 1, and R is a change rate linearly decreasing from 0.9 to 0.

$$R = 0.9 - t\left(\frac{0.9}{T_{max}}\right) \tag{12}$$

where t is the current iteration, and T_{max} is the maximum number of iterations. In the leader enhancement step, if the newly generated leader offers better fitness value, then the current leader will be replaced. Otherwise, the current leader is kept for the next iteration. The algorithm is repeated until the maximum number of iterations has reached. Finally, the global best alpha is known to be the optimal solution (best feature subset). The pseudocode of CBGWO can be found in [13].

2.4 Proposed competitive grey wolf optimizer

In the previous work, CBGWO was proven to be outperformed other conventional methods in feature selection. However, CBGWO is only applicable to binary optimization tasks, but not to the continuous optimization problems, which limits the functionality of CBGWO in many engineering applications. In this paper, we aim to model the CBGWO so that it can be useful for other continuous optimizations, as well as feature selection.

2.4.1 Initial population

The remodel approach is called competitive grey wolf optimizer (CGWO), which is a continuous version of CBGWO. Unlike CBGWO, the initialization of CGWO is given by

$$x_i^d = lb + (ub - lb)r_4 \tag{13}$$

where i is the order of wolf, d is the dimension of search space, r_4 is a random number distributed between 0 and 1, ub and lb are the upper and lower boundaries. As for feature selection, the parameters ub and lb are set at 1 and 0, respectively.

2.4.2 Position updating rule

Since CGWO is a continuous version of CBGWO, and thus the sigmoid function is no longer needed in the updating process. In CGWO, the position update of the loser is remodeling as follow:

$$x^d(t+1) = \frac{x_1^d + x_2^d + x_3^d}{3} \tag{14}$$

where x_1, x_2, and x_3 are computed using Eqs. (3), (4), and (5). In the process of leader enhancement, the random walk is formulated as:

$$L^d = \begin{cases} lb + (ub - lb)rand, & \text{if } R \geq r_5 \\ X_L^d, & \text{otherwise} \end{cases} \tag{15}$$

where $rand$ and r_5 are two independent random numbers distributed between 0 and 1, and R is computed using Eq. (12). The pseudocode of CGWO is presented in Algorithm 1.

2.5 Proposed opposition based competitive grey wolf optimizer

In the previous section, we have modeled the CBGWO into a continuous version of CGWO, which is now applicable to feature selection and other continuous optimization tasks. However, CGWO is simply a continuous version of CBGWO, which does not guarantee performance enhancement. Therefore, we propose a new opposition based competitive grey wolf optimizer (OBCGWO) to evolve the performance of CGWO in current work. The OBCGWO algorithm adopts the opposition based learning (OBL) strategy for performance enhancement.

Algorithm 1 Competitive Grey Wolf Optimizer

Input: N and T_{max}
1) Initialize a population of wolves using (13), x
2) Initialize the parameter y, A and C
3) Calculate the fitness of wolves, $F(x)$
4) Set x_α = The best wolf in population
$\quad\quad x_\beta$ = The second best wolf in population
$\quad\quad x_\delta$ = The third best wolf in population
5) **for** t = 1 to maximum number of iteration, T_{max}
6) $\quad$ Compute R as shown in (12)
$\quad\quad$ // Competition between each couple of wolves//
7) $\quad$ **for** i = 1 to half of population, $N/2$
8) $\quad\quad$ Randomly choose two wolves, x_k and x_m
9) $\quad\quad$ **if** $F(x_k)$ better than $F(x_m)$
10) $\quad\quad\quad x_w = x_k, x_l = x_m$
11) $\quad\quad$ **else**
12) $\quad\quad\quad x_w = x_m, x_l = x_k$
13) $\quad\quad$ **end if**
14) $\quad\quad$ Add x_w into new population
15) $\quad\quad$ Remove x_k and x_m from the population
16) $\quad$ **next** i
$\quad\quad$ // Update position of loser //
17) $\quad$ **for** i = 1 to half of the population, $N/2$
18) $\quad\quad$ Compute x_1, x_2 and x_3 as in (3), (4) and (5)
19) $\quad\quad$ Generate x_i^{new} by using (14)
20) $\quad\quad$ Evaluate the fitness of new wolf, $F(x_i^{new})$
21) $\quad\quad$ Add x_i^{new} into new population
22) $\quad$ **next** i
23) $\quad$ Update alpha, beta and delta
24) $\quad$ Update the parameter y, A and C
$\quad\quad$ // Leader enhancement strategy //
25) $\quad$ **for** j = 1 to 3 (number of leaders)
26) $\quad\quad$ Set $x_\alpha = X_L$
27) $\quad\quad$ Generate new leader, L_j using (15)
28) $\quad\quad$ Calculate fitness of new leader, $F(L_j)$
29) $\quad\quad$ Replace X_L with x_β (j=2) or x_δ (j=3)
30) $\quad$ **next** j
31) $\quad$ Update alpha, beta and delta based on new leaders
32) **next** t
Output: Global best alpha (Optimal feature subset)

2.5.1 Concept of opposition based learning

The OBL strategy is first introduced by Tizhoosh [28] to speed up the convergence behavior. According to literature, OBL was useful for improving the convergence of metaheuristic algorithms [29, 30]. Normally, metaheuristic algorithm generates a population of initial solution in a random manner. However, due to the lack of prior knowledge and experience, the algorithm cannot converge to the global optimum [31]. Therefore, integrating the OBL strategy into

CGWO is an effective and reliable way to resolve the above issue.

The concept of opposite number is explained as follow [28]: Given a real number X in an interval between ub and lb, and the opposite number $\overline{X}$ can be calculated as:

$$\overline{X} = ub + lb - X \tag{16}$$

In the multidimensional problem, the opposite solution of the solution X can be computed as [30]:

$$\overline{X}_j = ub_j + lb_j - X_j \tag{17}$$

where j is the dimension of search space.

2.5.2 The OBL based initialization

Algorithm 2 illustrates the pseudocode of the OBL based initialization strategy. The OBCGWO starts by generating a random population of N initial solutions, where N is the number of solutions. Afterward, OBL is applied to compute the opposite solution for each initial solution. The opposite and initial solutions are merged and sorted based on fitness values. Finally, the best N solutions that achieved better fitness values are used as the new initial solutions. In this way, a population of high quality initial solutions can be produced.

Algorithm 2 OBL Based Initialization Strategy

Input: Initial solutions, X
1) **for** (i = 1 to N)
2) $\quad$ **for** (d = 1 to D)
3) $\quad\quad$ Generate opposite solution $\overline{X}$ using (17)
4) $\quad$ **next** d
5) $\quad$ Evaluate the fitness value of opposite solution
6) **next** i
7) Merge current and opposite populations
8) Select the best N solutions to be the new initial solutions, X_{new}
Output: High quality initial solutions, X_{new}

2.5.3 The OBL based position update

Algorithm 3 presents the pseudocode of the OBL based position updating process. In comparison with losers, the winners (solution achieves better fitness value in the competition) are more capable of providing high quality solutions in their opposite directions. So, we only compute the opposite solutions of winners in OBCGWO algorithm. For OBCGWO, the opposite solution of winner is computed as follow:

$$\overline{X}_{w_j} = \begin{cases} lb_j + ub_j - X_{w_j}, & \text{if } r_6 > 0.5 \\ X_{w_j}, & \text{otherwise} \end{cases} \tag{18}$$

where X_w is the winner, r_6 is a random number distributed between 0 and 1, and j is the dimension. In OBCGWO, the opposite solutions are computed based on the probability, which intends to find preferable solutions while keeping some of the original information. The pseudocode of OBCGWO is shown in Algorithm 4.

Algorithm 3 OBL Based Position Update

Input: Winners of the competition, X_w

1) **for** (i = 1 to N)
2)   **for** (d = 1 to D)
3)   Generate opposite solution of winner using (18)
4)   **next** d
5)   Evaluate the fitness value of opposite solution
6) **next** i

Output: Opposite solutions

Algorithm 4 Opposition Based Competitive Grey Wolf Optimizer

Input: N and T_{max}

1) Initialize a population of wolves using (13), x
2) Initialize the parameter y, A and C
3) Calculate the fitness of wolves, $F(x)$
4) Compute a high quality population of wolves as in **Algorithm 2**
5) Set x_α = The best wolf in population
     x_β = The second best wolf in population
     x_δ = The third best wolf in population
6) **for** t = 1 to maximum number of iterations, T_{max}
7)   Compute R as shown in (12)
     // Competition between each couple of wolves//
8)   **for** i = 1 to half of population, N/2
9)   Randomly choose two wolves, x_k and x_m
10)   **if** $F(x_k)$ better than $F(x_m)$
11) $x_w = x_k, x_l = x_m$
12)   **else**
13) $x_w = x_m, x_l = x_k$
14)   **end if**
15)   Add x_w into new population
16)   Remove x_k and x_m from the population
17)   **next** i
     // Update position of loser //
18)   **for** i = 1 to half of the population, N/2
19)   Compute x_1, x_2 and x_3 as in (3), (4) and (5)
20)   Generate x_i^{new} by using (14)
21)   Evaluate the fitness of new wolf, $F(x_i^{new})$
22)   Add x_i^{new} into new population
23)   **next** i
24) Compute the opposite solution of winners as in **Algorithm 3**
25) Merge the winners, new losers and opposite solutions into a population
26) Keep the best N wolves from the merged population
27) Update alpha, beta and delta
28) Update the parameter y, A and C
     // Leader enhancement strategy //
29)   **for** j = 1 to 3 (number of leaders)
30)   Set $x_\alpha = X_L$
31)   Generate new leader, L_j using (15)
32)   Calculate fitness of new leader, $F(L_j)$
33)   Replace X_L with x_β (j=2) or x_δ (j=3)
34)   **next** j
35) Update alpha, beta and delta based on new leaders
36) **next** t

Output: Global best alpha (Optimal feature subset)

2.6 Application of proposed CGWO and OBCGWO for EMG feature selection

Due to the high dimensionality, the classification of EMG signals using all features is extremely difficult. This is mainly due to the existence of irrelevant and redundant features, which significantly degrades the performance of the classification model. Therefore, we employ the CGWO and OBCGWO to solve the feature selection problem in EMG signals classification. Note that the dimension of the search space is equal to the number of features. In the proposed scheme, each dimension is bounded between ub and lb. To determine whether the feature is selected or not, a simple technique that applies the static threshold is utilized, and it can be defined as follow [32]:

$$\begin{cases} x_i^d > 0.6, & \text{Selected feature} \\ x_i^d \leq 0.6, & \text{Unselected feature} \end{cases} \tag{19}$$

where x_i is the wolf at i order and d is the dimension of search space. Figure 1 illustrates a sample of a solution with the dimension of eight (a feature set that comprises of eight features). As can be observed, the 2nd, 3rd, 6th, and 7th features have the values of higher than 0.6, and thus these four features are selected in this sample solution.

Figure 2 exhibits the flow diagram of proposed methods for EMG feature selection and classification. In the first step, the features are extracted from the EMG signals to construct a feature set. After that, the CGWO and OBCGWO evaluate the relevant features from the feature set to form an optimal feature subset. As for feature selection, the fitness function that considered both classification performance and feature size are utilized to evaluate the individual solution, as shown in Eq. (20).

$$\downarrow \text{Fitness Function} = \alpha ER + (1-\alpha)\frac{|S|}{|R|} \tag{20}$$

where ER is the classification error rate computed by the k-nearest neighbor (KNN) algorithm, $|S|$ is the length of feature subset, $|R|$ is the total number of features, and α is a parameter to control the influence of classification performance and feature size. In this study, the EMG data are divided into 80% for the training set and 20% for the testing set. Finally, the features selected (optimal feature subset) by the CGWO and OBCGWO are fed into the KNN algorithm for the classification process. All the analysis is performed

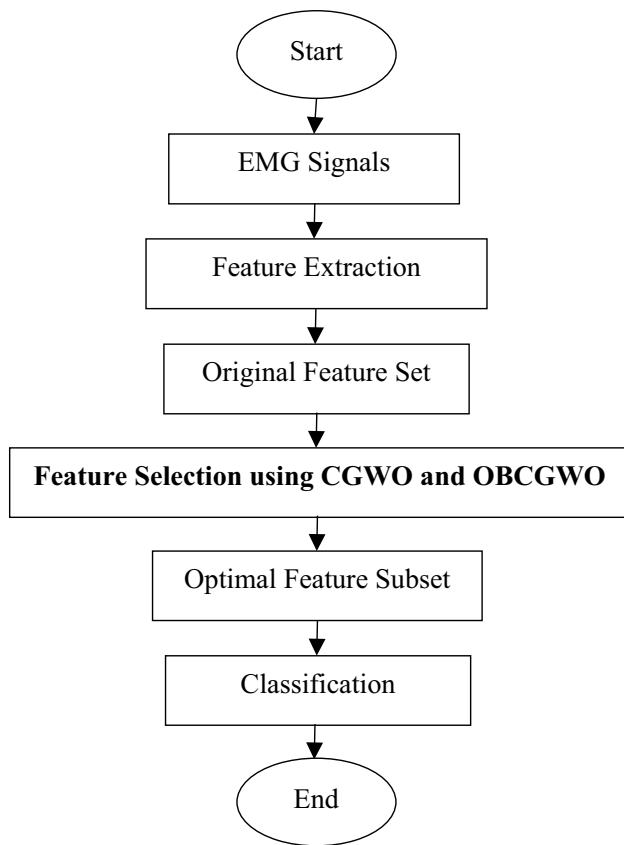| 1st	2nd	3rd	4th	5th	6th	7th	8th
0.43	**0.67**	**0.88**	0.12	0.34	**0.61**	**0.92**	0.23

Fig. 1 Example of a solution

Fig. 2 Flow diagram of proposed CGWO and OBCGWO for EMG pattern recognition

in MATLAB 9.4 using a computer with processing Intel Core i5-9400F CPU 2.90 GHz and 16 GB random access memory (RAM).

3 Results and discussion

The experiment is divided into two parts. First, the proposed methods are tested by solving the benchmark functions. Second, the proposed methods are applied to tackle the feature selection problem in EMG signals classification.

3.1 Evaluation metrics

Eight metrics include best fitness, worst fitness, mean fitness, standard deviation of fitness (STD), accuracy, feature size, feature selection ratio (FSR) and computational time (CT) are calculated to measure the performance of proposed algorithms in EMG feature selection.

- *Best fitness* It is the minimum solution found by the algorithm in the final set [33].
- *Worst fitness* It is the maximum solution obtained from the final set [33].
- *Mean fitness* It is the average value of all solutions in the final set [10].
- *Standard deviation of fitness (STD)* It is the standard deviation of all solutions in the final set [10].
- *Accuracy* It estimates how accurate the features selected by the feature selection method in EMG signals classification. It can be defined as the ratio of the number of correctly predicted samples to the total number of samples.
- *Feature size* It presents the number of features selected by the feature selection method in the final set.
- *Feature selection ratio (FSR)* It shows the ratio of the number of selected features obtained from the final set to the total number of original features [34].
- *Computational time (CT)* It implies how fast the processing speed of the feature selection method in the evaluation process.

The proposed algorithms are stochastic, which perform the search randomly. Thus each algorithm is repeated with 20 independent runs, using different random seeds. The evaluation metrics are calculated for each independent run. Finally, the average results obtained from 20 independent runs are recorded and displayed as the experimental results.

3.2 Experimental results of benchmark test

In the first part of the experiment, the numerical efficiency of proposed methods is tested by using 10 mathematical optimization problems [35, 36]. Table 2 depicts the description of 10 benchmark functions with their mathematical definitions. In this test, the proposed methods are compared with particle swarm optimization (PSO) [37] and flower pollination algorithm (FPA) [38]. Note that the population size (N) and maximum number of iterations (T_{max}) of each algorithm is set at 30 and 500 according to [35].

Table 3 outlines the results of the best, worst, mean, and STD of fitness values obtained from 10 benchmark functions. As can be seen, the proposed OBCGWO outperformed other algorithms in finding the best solution. The results clearly show the superiority of OBCGWO in optimization tasks. On the one hand, the convergence curves of the proposed methods are presented in Fig. 3. As can be seen, the proposed OBCGWO can always find the global optimal faster, which contributed to high convergence rate. For example, for function F4, F6, and F7, the OBCGWO converged faster than its competitors when searching for the preferable solution. The foremost cause of accelerated curves for OBCGWO is due to the trait that OBL learning

Table 2 Description of 10 benchmark functions

Function	Dimension	Range	f_{min}
$F_1(x) = \sum_{i=1}^{n} x_i^2$	30	$[-100, 100]$	0
$F_2(x) = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i|$	30	$[-10, 10]$	0
$F_3(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2$	30	$[-100, 100]$	0
$F_4(x) = \max\{|x_i|, \, 1 \leq i \leq n\}$	30	$[-100, 100]$	0
$F_5(x) = \sum_{i=1}^{n} \left[x_i^2 - 10 \cos(2\pi x_i) + 10 \right]$	30	$[-5.12 \; 5.12]$	0
$F_6(x) = -20 \exp\left(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2} \right) - \exp\left(\frac{1}{n} \sum_{i=1}^{n} \cos(2\pi x_i) \right) + 20 + e$	30	$[-32, 32]$	0
$F_7(x) = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}} \right) + 1$	30	$[-600, 600]$	0
$F_8(x) = \sum_{i=1}^{11} \left[a_i - \frac{x_1(b_i^2 + b_i x_2)}{b_i^2 + b_i x_3 + x_4} \right]^2$	4	$[-5, 5]$	0.0003
$F_9(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1 x_2 - 4x_2^2 + 4x_2^4$	2	$[-5, 5]$	-1.0316
$F_{10}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6 \right)^2 + 10\left(1 - \frac{1}{8\pi} \right)\cos x_1 + 10$	2	$[-5, 5]$	0.3980

improves the quality of initial solutions and enhances the explorative behavior of the algorithm.

3.3 Experimental results of EMG feature selection

In the second part of the experiment, the effectiveness of proposed methods in EMG feature selection is examined. Remark, the EMG signals of ten different hand and wrist motions were collected from eight subjects. After that, the windowing was applied, and thirty features were extracted from each EMG segment. Then, we utilize the proposed CGWO and OBCGWO algorithms to find the optimal feature subset. However, it is interesting to know whether proposed algorithms can provide promising performance in feature selection. For such reason, four recent and popular algorithms include PSO [37], butterfly optimization algorithm (BOA) [39], FPA [38], and competitive binary grey wolf optimizer (CBGWO) [13] are used to investigate the efficacy and reliable of proposed algorithms in this work.

The parameter settings of feature selection methods are described as follows: To ensure all the algorithms conducted in the same condition, the population size (N) and maximum number of iteration (T_{max}) are set at 50 and 100, respectively. Besides, we set the α to 0.9 since the classification performance is the most important measure. As for PSO, the acceleration coefficient c_1 and c_2 are set at 1.49618, and the inertia weight w is fixed at 0.7298. For FPA, the switch probability P is set at 0.8. For BOA, the modular modality c and switch probability p are set to 0.01 and 0.8, respectively. Note that there is no additional parameter setting for CBGWO, CGWO, and OBCGWO.

Table 4 demonstrates the experimental results of the best, worst, mean, and STD of fitness values on eight subjects. On the one hand, the convergence curves of proposed methods on eight subjects are shown in Fig. 4. In Table 4, the best results are highlighted with bold text. Note that the lower the best, worst, mean, and STD values are, the better the performance of the feature selection method is. As can be observed, OBCGWO scored the optimal properties in most of the datasets (six subjects). The results show that OBCGWO outperformed CGWO, CBGWO, BOA, PSO, and FPA in evaluating the most informative feature subset.

From Table 4, OBCGWO perceived the lowest worst fitness in at least six subjects. Owing to OBL based initialization strategy, OBCGWO can be capable to enhance the quality of initial solutions and can effectively obtain the best solution in feature selection. On the other hand, CGWO was also presenting competitive results. Although CGWO was slightly worse than OBCGWO, however, its performance was much better than BOA, FPA and PSO.

Table 5 presents the experimental results of the accuracy, feature size, FSR, and computational cost on eight subjects. In Table 5, the best result for each algorithm is highlighted. Inspecting the result, OBCGWO achieved the highest average accuracy on five subjects, which overtook other competitors in current work. On the one hand, BOA was found to be the worst method that offered lower accuracy on most of the subjects.

In comparison with OBCGWO and CGWO, CBGWO was highly capable of reducing the number of features. From Table 5, CBGWO was showing the optimal performance in feature reduction, which achieved the lowest feature size and FSR values in most subjects. On the other hand, OBCGWO

Table 3 Comparison of optimization results obtained from the 10 benchmark functions

Function	Metrics	Algorithm			
		OBCGWO	CGWO	FPA	PSO
F1	Best fitness	9.77E−34	9.29E−26	745.8057	5.51E−07
	Worst fitness	1.97E−30	4.62E−23	2156.321	8.54E−05
	Mean fitness	2.68E−31	5.83E−24	1376.070	1.27E−05
	STD	4.79E−31	1.14E−23	366.7402	2.04E−05
F2	Best fitness	9.78E−21	1.35E−15	27.95599	0.00075
	Worst fitness	1.45E−18	3.38E−14	57.59586	40.00041
	Mean fitness	2.25E−19	8.70E−15	37.59144	12.51678
	STD	3.96E−19	7.89E−15	9.190213	11.64099
F3	Best fitness	1.77E−11	0.002554	1164.934	369.951
	Worst fitness	0.657087	2.491397	2915.047	28585.17
	Mean fitness	0.036805	0.305382	1910.456	7159.633
	STD	0.146963	0.603044	473.1942	6323.635
F4	Best fitness	1.41E−14	1.93E−07	17.39516	3.133562
	Worst fitness	1.11E−10	6.07E−05	29.64983	16.59651
	Mean fitness	7.39E−12	1.63E−05	23.50523	9.566046
	STD	2.47E−11	1.82E−05	3.203809	3.297489
F5	Best fitness	0	5.68E−14	98.69032	59.69739
	Worst fitness	21.54373	20.7833	169.7761	182.1475
	Mean fitness	1.269122	3.032385	130.4977	111.3718
	STD	4.808746	5.765003	20.17553	33.85994
F6	Best fitness	4.44E−15	1.47E−13	10.21737	0.000578
	Worst fitness	2.93E−14	6.55E−13	13.87377	14.37459
	Mean fitness	1.46E−14	3.51E−13	12.06299	1.960848
	STD	7.04E−15	1.33E−13	1.082126	3.052565
F7	Best fitness	0	0	8.425069	1.58E−06
	Worst fitness	0	0.025828	20.20135	0.083606
	Mean fitness	0	0.002538	13.39414	0.020501
	STD	0	0.007814	3.431041	0.028379
F8	Best fitness	0.000308	0.000454	0.000517	0.000307
	Worst fitness	0.001225	0.020363	0.001244	0.020363
	Mean fitness	0.000717	0.001627	0.000831	0.006121
	STD	0.000242	0.004411	0.000184	0.008610
F9	Best fitness	−1.03163	−1.03163	−1.03163	−1.03163
	Worst fitness	−1.03113	−1.03163	−1.03163	−1.03163
	Mean fitness	−1.03151	−1.03163	−1.03163	−1.03163
	STD	0.000129	3.98E−07	2.19E−09	2.10E−16
F10	Best fitness	0.397887	0.397887	0.397887	0.397887
	Worst fitness	0.399582	0.415318	0.397888	0.397887
	Mean fitness	0.397996	0.398975	0.397887	0.397887
	STD	0.000379	0.003962	4.66E−08	0

and CGWO yielded the optimal feature size and FSR on two and three subjects, respectively. Even though CBGWO is good in feature reduction, however, the relevant feature might be eliminated and thus resulting in unsatisfactory performance.

As for computational time (CT), the fastest processing speed was achieved by CGWO and CBGWO. This is expected because CBGWO and CGWO employ the competition strategy that only updates the position of losers (half of the population) in the process of evaluation. Based on the results obtained, OBCGWO yielded high computation time in most subjects. The additional computational cost of OBCGWO is mainly coming from the OBL based position update, which spends more time to evaluate the opposite
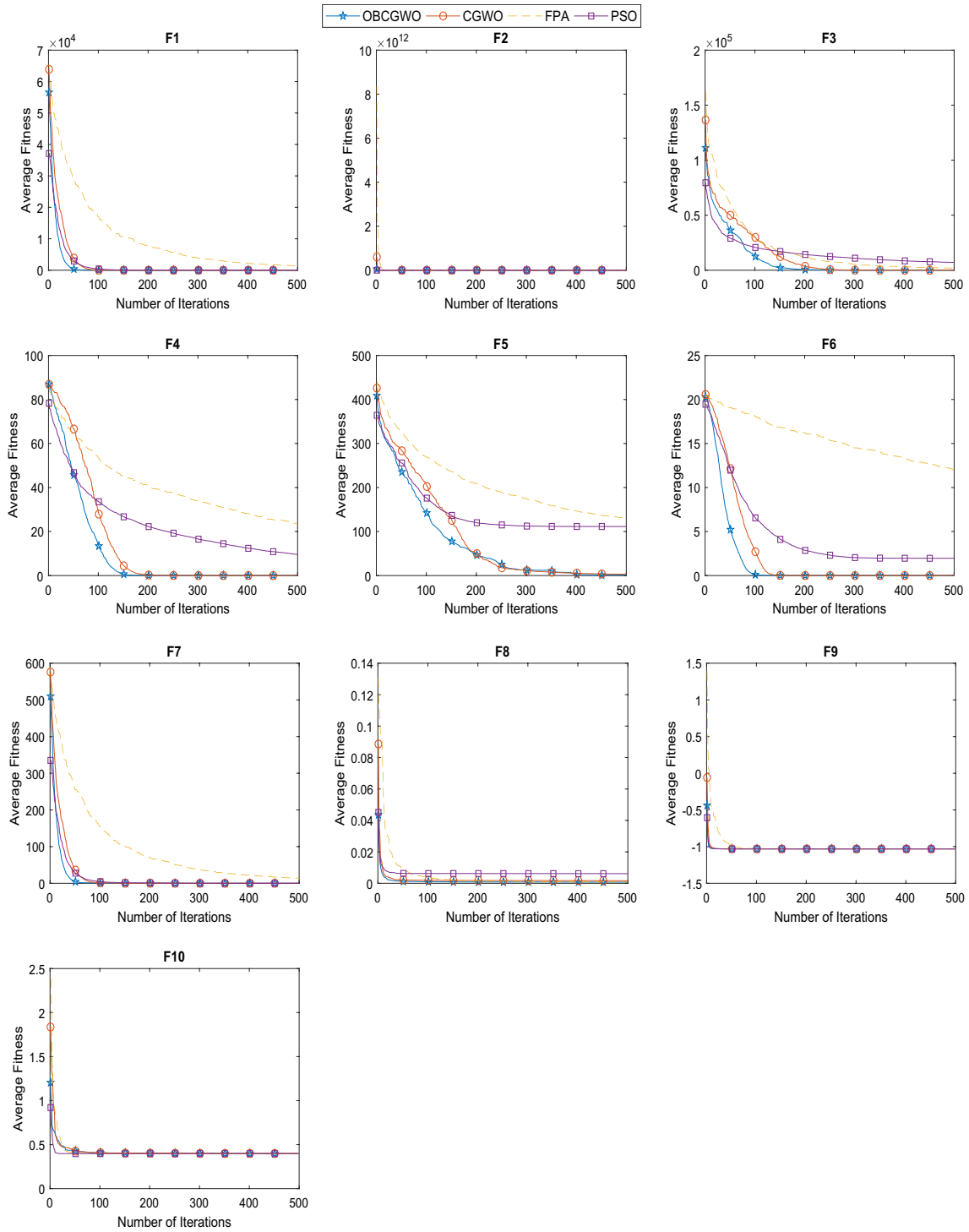
Fig. 3 Convergence curves of proposed methods on 10 benchmark functions

Table 4 Experimental results of the best, worst, mean, and STD of fitness values on eight subjects

Dataset	Metrics	Algorithm					
		OBCGWO	CGWO	BOA	CBGWO	FPA	PSO
Subject 1	Best fitness	**0.0097**	0.0105	0.0405	**0.0097**	0.0453	0.0293
	Worst fitness	**0.0563**	0.0607	0.0929	**0.0563**	0.0858	0.0746
	Mean fitness	**0.0348**	0.0362	0.0659	0.0355	0.0664	0.0520
	STD	0.0131	0.0134	0.0133	0.0129	**0.0123**	0.0139
Subject 2	Best fitness	0.0327	**0.0312**	0.0791	0.0386	0.0658	0.0559
	Worst fitness	0.1059	0.1059	0.1266	**0.1051**	0.1353	0.1291
	Mean fitness	0.0624	**0.0613**	0.1034	0.0652	0.0944	0.0793
	STD	0.0172	0.0192	**0.0154**	0.0180	0.0181	0.0179
Subject 3	Best fitness	**0.0467**	0.0519	0.0848	**0.0467**	0.0755	0.0611
	Worst fitness	**0.1036**	0.1074	0.1531	0.1059	0.1386	0.1293
	Mean fitness	0.0757	0.0763	0.1159	**0.0752**	0.1082	0.0944
	STD	0.0151	0.0158	0.0210	**0.0150**	0.0180	0.0183
Subject 4	Best fitness	**0.0023**	**0.0023**	0.0299	**0.0023**	0.0341	0.0174
	Worst fitness	**0.0328**	0.0482	0.1134	0.0585	0.0785	0.0906
	Mean fitness	**0.0056**	0.0087	0.0710	0.0194	0.0528	0.0469
	STD	**0.0071**	0.0137	0.0266	0.0207	0.0109	0.0247
Subject 5	Best fitness	**0.0053**	0.0061	0.0404	0.0105	0.0458	0.0159
	Worst fitness	**0.1043**	0.1051	0.1431	0.1066	0.1258	0.1210
	Mean fitness	**0.0242**	0.0452	0.1011	0.0664	0.0717	0.0742
	STD	0.0270	0.0385	0.0266	0.0295	**0.0218**	0.0343
Subject 6	Best fitness	**0.0023**	0.0038	0.0500	0.1001	0.0438	0.0247
	Worst fitness	**0.1325**	0.1731	0.2343	0.1775	0.1856	0.2024
	Mean fitness	**0.0316**	0.1274	0.1484	0.1365	0.1134	0.1323
	STD	0.0425	0.0444	0.0600	**0.0208**	0.0468	0.0616
Subject 7	Best fitness	0.0852	**0.0844**	0.1324	0.0852	0.1242	0.0996
	Worst fitness	0.1576	0.1620	0.2195	**0.1561**	0.1880	0.1727
	Mean fitness	0.1257	0.1243	0.1707	**0.1224**	0.1600	0.1414
	STD	0.0214	0.0221	0.0268	0.0218	**0.0205**	0.0232
Subject 8	Best fitness	**0.0342**	0.0438	0.0931	0.0350	0.0718	0.0635
	Worst fitness	**0.1043**	0.1059	0.1730	**0.1043**	0.1360	0.1542
	Mean fitness	0.0805	0.0827	0.1294	**0.0798**	0.1170	0.1034
	STD	0.0168	0.0159	0.0184	0.0160	**0.0150**	0.0191

solution of winners. However, OBCGWO can usually find the relevant features that contributed to the highest accuracy in EMG signals classification.

Furthermore, the statistical *t* test is applied to examine whether the classification performance of the proposed OBCGWO is significantly better than other methods. Table 6 presents the result of the *t*-test with *p*-values. Note that the OBCGWO is used as the reference algorithm in this test. As can be seen, the classification performance of OBCGWO was significantly better than BOA, PSO, FPA, and CBGWO in most cases (p value < 0.05). The results again validate the effectiveness of proposed OBCGWO in EMG feature selection. The reason for the superior performance of OBCGWO

is that the OBL strategy is equipped for both initialization and position update. The OBL based initialization enhances the quality of initial solutions, while the OBL based position update tends to improve the explorative behavior of the algorithm. Thanks to these interesting properties, OBCGWO can efficiently find the best solution and avoid the local optimal.

Figure 5 illustrates the result of the total number of times each feature (from 1 to 30) selected by the proposed OBCGWO for all eight subjects and four channels across 20 independent runs. One can see that the features that are mostly selected by OBCGWO are SSC (307), WA (289), IEMG (155), CARD (124), AR (88), and EWL (67) features. As compared to FD features, the result indicates that
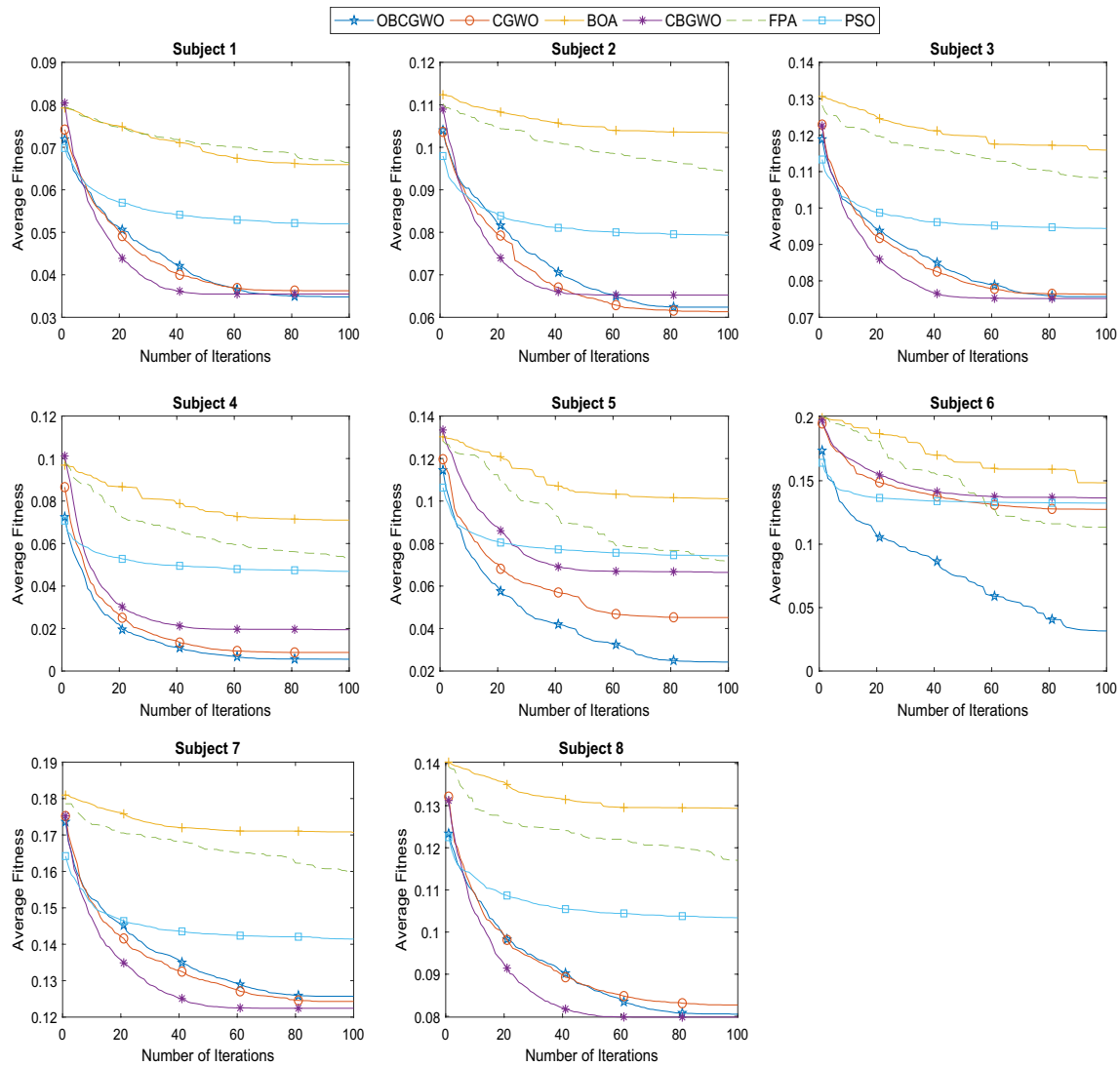
Fig. 4 Convergence curves of proposed methods on 8 subjects

TD features can often provide useful signal information for discriminating the hand and wrist motions.

In this paper, we have proposed the CGWO and OBCGWO algorithms to tackle the feature selection problem in EMG signals classification. The proposed OBCGWO not only beneficial in EMG feature selection but also showing good performance in several benchmark tests. Our results showed that OBCGWO was able to provide promising performance in EMG signals classification. The OBCGWO worked significantly better than BOA, PSO, FPA, and CBGWO in finding the optimal feature subset. In short, OBCGWO is a useful tool, and it can be applied to other applications.

4 Conclusion

Feature selection is one of the effective ways to reduce the redundancy in the feature set. Wrapper based feature selection not only helps to minimize the feature size but also improves the accuracy of the system. In this regard, an opposition based competitive grey wolf optimizer (OBCGWO) is proposed to solve the feature selection problem in EMG signals classification. In comparison with PSO, FPA, BOA, CGWO, and CBGWO, OBCGWO can usually select the significant features, thus leading to the highest classification performance. According to the findings, OBCGWO may be treated as a valuable decision support tool. In the future,

Table 5 Experimental results of the accuracy, feature size, FSR, and CT on eight subjects

Dataset	Metrics	Algorithm					
		OBCGWO	CGWO	BOA	CBGWO	FPA	PSO
Subject 1	Avg. accuracy (%)	**96.67**	96.49	95.26	96.58	96.44	96.38
	Avg. feature size	6.35	**6.20**	30.70	**6.20**	45.35	25.65
	Avg. FSR	0.0481	**0.0470**	0.2326	**0.0470**	0.3436	0.1943
	Avg. CT (s)	10.248	5.699	9.234	**5.378**	9.858	9.546
Subject 2	Avg. accuracy (%)	93.65	**93.76**	91.87	93.30	93.28	93.33
	Avg. feature size	6.90	6.85	39.90	**6.55**	44.75	25.50
	Avg. FSR	0.0523	0.0519	0.3023	**0.0496**	0.339	0.1932
	Avg. CT (s)	10.109	5.305	9.502	**5.187**	10.069	9.350
Subject 3	Avg. accuracy (%)	92.30	92.21	90.49	**92.33**	92.13	91.95
	Avg. feature size	8.40	8.20	40.00	**8.05**	49.30	29.00
	Avg. FSR	0.0636	0.0621	0.3030	**0.0610**	0.3735	0.2197
	Avg. CT (s)	9.980	**5.183**	9.079	5.203	10.111	9.132
Subject 4	Avg. accuracy (%)	**99.77**	99.45	94.89	98.39	97.87	97.39
	Avg. feature size	**4.60**	5.05	33.00	6.55	44.45	30.85
	Avg. FSR	**0.0348**	0.0383	0.2500	0.0496	0.3367	0.2337
	Avg. CT (s)	9.976	5.410	9.170	**5.317**	10.006	9.809
Subject 5	Avg. accuracy (%)	**98.02**	95.60	91.70	93.39	96.01	94.11
	Avg. feature size	8.40	**7.40**	34.80	9.15	47.25	28.00
	Avg. FSR	0.0636	**0.0561**	0.2636	0.0693	0.358	0.2121
	Avg. CT (s)	10.052	**5.237**	9.618	5.318	10.181	9.451
Subject 6	Avg. accuracy (%)	**97.39**	86.75	86.49	85.80	91.84	88.05
	Avg. feature size	**10.65**	10.85	35.40	11.50	52.70	32.65
	Avg. FSR	**0.0807**	0.0822	0.2682	0.0871	0.3992	0.2473
	Avg. CT (s)	10.395	**5.220**	8.845	5.342	9.938	9.310
Subject 7	Avg. accuracy (%)	86.87	86.93	84.43	**87.16**	86.18	86.75
	Avg. feature size	9.95	**8.75**	40.30	9.00	46.95	29.30
	Avg. FSR	0.0754	**0.0663**	0.3053	0.0682	0.3557	0.2220
	Avg. CT (s)	10.194	5.241	8.921	**5.087**	10.072	9.321
Subject 8	Avg. accuracy (%)	**91.90**	91.55	89.02	91.87	90.89	91.15
	Avg. feature size	10.00	8.80	40.35	**8.75**	46.25	31.35
	Avg. FSR	0.0758	0.0667	0.3057	**0.0663**	0.3504	0.2375
	Avg. CT (s)	10.832	**5.168**	9.100	5.318	10.277	9.439

Table 6 Experimental result of t-test with p values

| Dataset	p values				
	CGWO	BOA	CBGWO	FPA	PSO
Subject 1	0.029815	2.98E−05	0.082814	0.007523	0.014089
Subject 2	0.680988	6.21E−05	0.319305	0.242958	0.012118
Subject 3	0.379263	2.15E−05	0.715682	0.137180	0.143659
Subject 4	0.374456	4.24E−07	0.010163	5.55E−07	0.000680
Subject 5	0.011843	6.50E−09	4.70E−06	0.006978	0.000142
Subject 6	8.04E−06	5.37E−07	2.17E−08	0.000472	9.19E−05
Subject 7	0.705403	5.99E−07	0.046747	0.001725	0.618187
Subject 8	0.006733	1.48E−07	0.789428	2.35E−05	0.012415
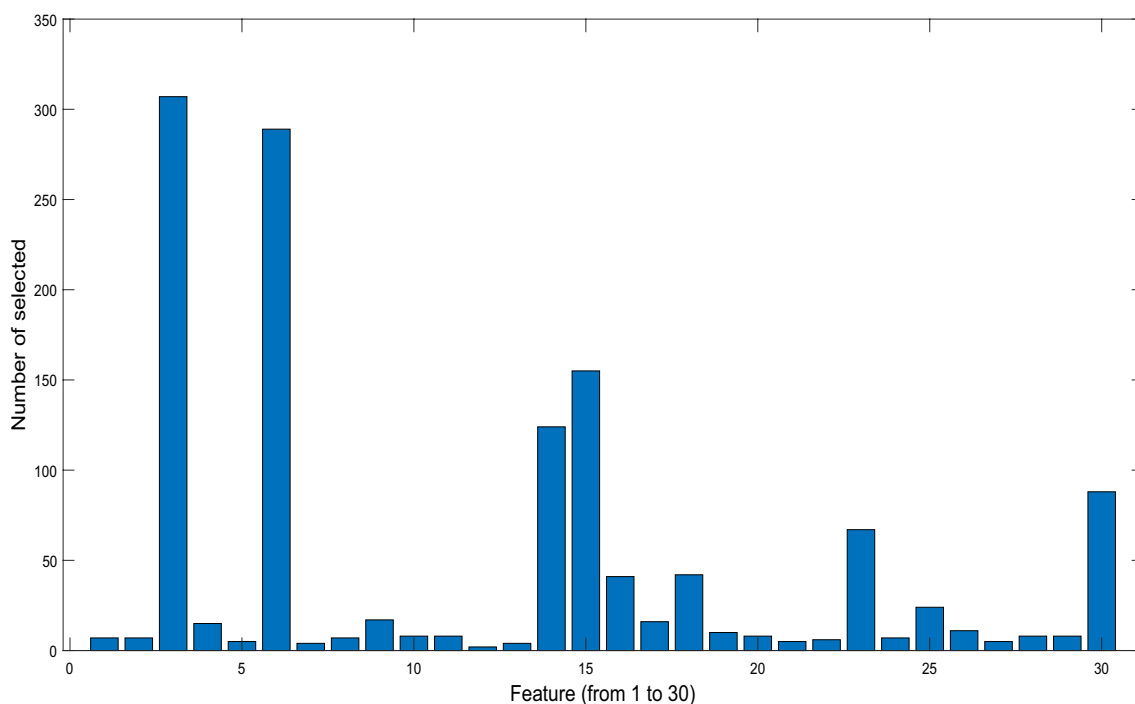
Fig. 5 Result of the total number of times each feature (from 1 to 30) selected using OBCGWO

OBCGWO can be used in other continuous optimization tasks such as numerical optimization, optimized support vector machine, and neural network.

Authors contribution Conceptualization: JT; methodology: JT; formal analysis and investigation: JT; writing—original draft preparation: JT; writing—review and editing: JT, ARA; supervision: ARA.

Compliance with ethical standards

Conflict of interest Both the authors declare that there is no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Waris A, Kamavuako EN (2018) Effect of threshold values on the combination of EMG time domain features: surface versus intramuscular EMG. Biomed Signal Process Control 45:267–273. https://doi.org/10.1016/j.bspc.2018.05.036
2. Waris A, Niazi IK, Jamil M et al (2018) Multiday evaluation of techniques for EMG based classification of hand motions. IEEE J Biomed Health Inform. https://doi.org/10.1109/JBHI.2018.2864335
3. Tavakoli M, Benussi C, Lourenco JL (2017) Single channel surface EMG control of advanced prosthetic hands: a simple, low cost and efficient approach. Expert Syst Appl 79:322–332. https://doi.org/10.1016/j.eswa.2017.03.012
4. Khushaba RN, Al-Timemy AH, Al-Ani A, Al-Jumaily A (2017) A framework of temporal-spatial descriptors-based feature extraction for improved myoelectric pattern recognition. IEEE Trans Neural Syst Rehabil Eng 25:1821–1831. https://doi.org/10.1109/TNSRE.2017.2687520
5. Bharti KK, Singh PK (2016) Opposition chaotic fitness mutation based adaptive inertia weight BPSO for feature selection in text clustering. Appl Soft Comput 43:20–34. https://doi.org/10.1016/j.asoc.2016.01.019
6. Lin K-C, Hung JC, Wei J (2018) Feature selection with modified lion's algorithms and support vector machine for high-dimensional data. Appl Soft Comput 68:669–676. https://doi.org/10.1016/j.asoc.2018.01.011
7. Xue B, Zhang M, Browne WN (2013) Particle swarm optimization for feature selection in classification: a multi-objective approach. IEEE Trans Cybern 43:1656–1671. https://doi.org/10.1109/TSMCB.2012.2227469
8. Papa JP, Rosa GH, de Souza AN, Afonso LCS (2018) Feature selection through binary brain storm optimization. Comput Electr Eng 72:468–481. https://doi.org/10.1016/j.compeleceng.2018.10.013
9. Ramos CCO, Souza AN, Chiachia G et al (2011) A novel algorithm for feature selection using Harmony Search and its application for non-technical losses detection. Comput Electr Eng 37:886–894. https://doi.org/10.1016/j.compeleceng.2011.09.013
10. Emary E, Zawbaa HM, Hassanien AE (2016) Binary grey wolf optimization approaches for feature selection. Neurocomputing 172:371–381. https://doi.org/10.1016/j.neucom.2015.06.083
11. Ewees AA, Aziz MAE, Hassanien AE (2017) Chaotic multi-verse optimizer-based feature selection. Neural Comput Appl. https://doi.org/10.1007/s00521-017-3131-4
12. Tan TY, Zhang L, Neoh SC, Lim CP (2018) Intelligent skin cancer detection using enhanced particle swarm optimization.

Knowl-Based Syst 158:118–135. https://doi.org/10.1016/j.knosys.2018.05.042

13. Too J, Abdullah AR, Mohd Saad N et al (2018) A new competitive binary grey wolf optimizer to solve the feature selection problem in EMG signals classification. Computers 7:58. https://doi.org/10.3390/computers7040058

14. biopatrec/biopatrec. In: GitHub. https://github.com/biopatrec/biopatrec. Accessed 2 Oct 2019

15. Mastinu E, Ortiz-Catalan M, Håkansson B (2015) Analog front-ends comparison in the way of a portable, low-power and low-cost EMG controller based on pattern recognition. In: 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC), pp 2111–2114

16. Wang N, Lao K, Zhang X (2017) Design and myoelectric control of an anthropomorphic prosthetic hand. J Bionic Eng 14:47–59. https://doi.org/10.1016/S1672-6529(16)60377-3

17. Powar OS, Chemmangat K, Figarado S (2018) A novel pre-processing procedure for enhanced feature extraction and characterization of electromyogram signals. Biomed Signal Process Control 42:277–286. https://doi.org/10.1016/j.bspc.2018.02.006

18. Phinyomark A, Phukpattaranont P, Limsakul C (2012) Feature reduction and selection for EMG signal classification. Expert Syst Appl 39:7420–7431. https://doi.org/10.1016/j.eswa.2012.01.102

19. Xiao F, Wang Y, Gao Y et al (2018) Continuous estimation of joint angle from electromyography using multiple time-delayed features and random forests. Biomed Signal Process Control 39:303–311. https://doi.org/10.1016/j.bspc.2017.08.015

20. Hudgins B, Parker P, Scott RN (1993) A new strategy for multi-function myoelectric control. IEEE Trans Biomed Eng 40:82–94. https://doi.org/10.1109/10.204774

21. Mesa I, Rubio A, Tubia I et al (2014) Channel and feature selection for a surface electromyographic pattern recognition task. Expert Syst Appl 41:5190–5200. https://doi.org/10.1016/j.eswa.2014.03.014

22. Thongpanja S, Phinyomark A, Phukpattaranont P, Limsakul C (2013) Mean and median frequency of EMG signal to determine muscle force based on time-dependent power spectrum. Elektron ir Elektrotechnika 19:51–56. https://doi.org/10.5755/j01.eee.19.3.3697

23. Too J, Abdullah AR, Saad NM (2019) Classification of hand movements based on discrete wavelet transform and enhanced feature extraction. Int J Adv Comput Sci Appl IJACSA. https://doi.org/10.14569/IJACSA.2019.0100612

24. Ortiz-Catalan M (2015) Cardinality as a highly descriptive feature in myoelectric pattern recognition for decoding motor volition. Front Neurosci. https://doi.org/10.3389/fnins.2015.00416

25. Phinyomark A, Quaine F, Charbonnier S et al (2014) Feature extraction of the first difference of EMG time series for EMG pattern recognition. Comput Methods Programs Biomed 117:247–256. https://doi.org/10.1016/j.cmpb.2014.06.013

26. Phinyomark A, Quaine F, Charbonnier S et al (2013) EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Syst Appl 40:4832–4840. https://doi.org/10.1016/j.eswa.2013.02.023

27. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. Adv Eng Softw 69:46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

28. Tizhoosh HR (2006) Opposition-based reinforcement learning. J Adv Comput Intell Intell Inform 10:578–585. https://doi.org/10.20965/jaciii.2006.p0578

29. Abd Elaziz M, Oliva D, Xiong S (2017) An improved opposition-based sine cosine algorithm for global optimization. Expert Syst Appl 90:484–500. https://doi.org/10.1016/j.eswa.2017.07.043

30. Ibrahim RA, Elaziz MA, Lu S (2018) Chaotic opposition-based grey-wolf optimization algorithm based on differential evolution and disruption operator for global optimization. Expert Syst Appl 108:1–27. https://doi.org/10.1016/j.eswa.2018.04.028

31. Dinkar SK, Deep K (2018) Accelerated opposition-based ant-lion optimizer with application to order reduction of linear time-invariant systems. Arab J Sci Eng. https://doi.org/10.1007/s13369-018-3370-4

32. Xue B, Zhang M, Browne WN (2014) Particle swarm optimisation for feature selection in classification: novel initialisation and updating mechanisms. Appl Soft Comput 18:261–276. https://doi.org/10.1016/j.asoc.2013.09.018

33. Zawbaa HM, Emary E, Grosan C, Snasel V (2018) Large-dimensionality small-instance set feature selection: a hybrid bio-inspired heuristic approach. Swarm Evol Comput 42:29–42. https://doi.org/10.1016/j.swevo.2018.02.021

34. Tawhid MA, Dsouza KB (2018) Hybrid binary bat enhanced particle swarm optimization algorithm for solving feature selection problems. Appl Comput Inform. https://doi.org/10.1016/j.aci.2018.04.001

35. Mirjalili S, Lewis A (2016) The whale optimization algorithm. Adv Eng Softw 95:51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

36. Shadravan S, Naji HR, Bardsiri VK (2019) The sailfish optimizer: a novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems. Eng Appl Artif Intell 80:20–34. https://doi.org/10.1016/j.engappai.2019.01.001

37. Shi Y, Eberhart R (1998) A modified particle swarm optimizer. In: 1998 IEEE international conference on evolutionary computation proceedings. IEEE world congress on computational intelligence (Cat. No. 98TH8360). pp 69–73

38. Yang X-S (2012) Flower pollination algorithm for global optimization. In: Durand-Lose J, Jonoska N (eds) Unconventional computation and natural computation. Springer, Berlin, pp 240–249

39. Arora S, Singh S (2018) Butterfly optimization algorithm: a novel approach for global optimization. Soft Comput. https://doi.org/10.1007/s00500-018-3102-4